**Analyzing Potential Influences on Seismic Sensor**

**Vibration Signals for Enhanced Detection Accuracy**

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| **Abstract** In the flied of seismic data collection, several factors influence the quality and accuracy of recorded signals. These factors include the nature of the data collection environment, including the speed of wave propagation and the resulting wave amplitudes. Noise, both from the instrumentation and the target of interest, It is a big challenge in signal fidelity. Additionally, the presence of false signals requesting rigorous data validation. Deploying sensors strategically to match their sensing capabilities is paramount. These considerations collectively shape the integrity and reliability of seismic data, crucial for object detection monitoring. This research delves into elucidating the prevalent factors responsible for signal distortion. It stems from an experimental investigation carried out across four distinct terrains – mud, soil, grass, and asphalt – on a farm setting. Within each of these environments, four distinct target types were identified: human, animal, motorbike, and car. Each target exhibited unique trajectories and movements tailored to its specific environment. This study closely monitored fundamental influences on seismic signal waves, revealing that the surface's elasticity resulted in wave amplitudes approximately as follows when compared to asphalt: (25% grass 90%, soil 40%, and muddy 65%). The variance in these values can be attributed to a multitude of factors that exert an influence on the signal that will explain in detail in this paper. |
| ***Keywords:*** *Deployment of sensors, Environments, Noisy, False Alarms* |

1. Introduction

****Seismic data collection forms the mean of numerous critical applications, ranging from earthquake monitoring to detection for human, animal vibration analysis. The accuracy and reliability of the recorded seismic signals are paramount, as they provide informed make a decision and early warning systems. However, this accuracy depends on a complex interplay of factors that affect data quality. The environmental characteristics, including wave propagation speed [1] and wave amplitudes, shape the signals captured by seismic sensors. Moreover, the persistent challenge of noise generated [2] from both instrumentation and the observed target a significant hurdle in maintaining signal fidelity as shown in Figure 1. Additionally, the omnipresent issue of false signals required stringent data validation procedures[3]. To further compound the matter, strategic sensor deployment becomes imperative to align their sensing capabilities with the specific monitoring objectives. In response to these challenges, this paper embarks on a comprehensive analysis of the effects influencing seismic data collection. It the critical importance of the data collection environment, explores noise reduction strategies, false signal identification, and outlines best practices for strategic sensor deployment[4]. Furthermore, this work combines solutions collected from a multi published research, offering a strategic roadmap for optimizing seismic data collection. Through a systematic examination of these factors, this research aims to enhance the integrity and reliability of seismic data, serving as a foundational resource for object detection and monitoring in diverse applications.

**Figure 1.** Potential influences on the vibration signal.

In this paper, we will discuss four sections. The first section addresses the Seismic sensor and deploying of it, the second section Environment for Data Collection, focusing on how different environments impact the signal, including the effects on signal speed and amplitude. In the three section, we delve into Signal Noise, examining both the noise originating from the target itself and the noise emanating from the observed object. Finally, in the forth section, we explore the topic of false signals, which can arise due to instrument damage and other pertinent factors.

1. Seismic Sensor

A seismic sensor, as depicted as shown in (Figure 2 (a and b)), can utilize both accelerometers and geophones to identify seismic signals produced by moving objects. Accelerometers, employing microelectromechanical system (MEMS) technology, are typically lightweight and compact. On the other hand, geophones, such as coil geophones, generate a voltage proportional to seismic velocity through electromagnetic induction, requiring no energy consumption. Due to their high sensitivity and energy-efficient nature, coil geophones are widely adopted for moving target recognition. Coil geophones come in two variants: single-axis geophones, which sense the vertical seismic component, and three-axis geophones, which can detect both horizontal and vertical components. A three-axis geophone comprises three sensor elements placed orthogonally to capture the 3-D velocity of seismic signals[5].

**Figure 2.** a. Geophone sensor[6]. b. Accelerometer sensor[7].

1. Deploying of sensor:

Given that the quality of the signals received from sensors plays a crucial role in obtaining accurate data related to the target[6], this section will address the potential issues researchers may face when working with seismic sensors designed for target detection. In our study, we utilized 8 Geophone - SM-24 sensors, strategically positioned in a specific configuration. The placement ensured that there was a minimum distance of one meter between each sensor and a maximum distance of three meters throughout the designated environment, as illustrated in the accompanying as shown in Figure 3**.**

**Figure 3.** Environment for the experiment.

One of the most common problems that a researcher may face regarding the signal generated by seismic sensors is the process of connecting the sensors to each other. In this research, two nodes were connected, each node representing a receiver from four sensors, in which four pieces of ADC 115 were used to convert the signal from analog to digital so that it could be processed through the used Raspberry PI 3. One of the most important notes in this linking is that it uses a library that depends on the difference between two inputs, 0 and 1, so the remaining three were linked based on the (Table 1)shown below.

**Table 1.** I2C Addressing.

|  |  |
| --- | --- |
| **I2C Addressing** | **I2C ADDER** |
| 0×48 | GND |
| 0×49 | VIN |
| 0×4A | SDA |
| 0×4B | SCL |

The ADS11x5 chips come with a default 7-bit I2C address of 0x48 (1001000). However, they also offer a clever addressing scheme that enables you to select from four different addresses using a single address pin, referred to as ADR (ADdRess).

1. Environment for Data Collection

The environment in which seismic data is collected constitutes a critical determinant of data quality and accuracy. This section delves into the profound influence of various environmental factors on seismic signals, shedding light on the intricacies of signal propagation, speed, and amplitude. The transmission speed of mechanical signals in different media can be described by the equation for wave propagation, which is dependent on the properties of the medium[8]. The equation that governs the speed of mechanical waves, such as sound waves or seismic waves, is:

 $v=\sqrt{\frac{T}{μ}}$ (1)

Where V is the wave velocity, T is the tension or stiffness of the medium, M is the mass per unit length of the medium. This equation illustrates how the transmission speed of mechanical waves is related to the tension and the mass per unit length of the medium. In different media, such as solids, liquids, or gases, these properties vary significantly, leading to variations in wave transmission speed. For example, in a solid material like steel, which has a high tension and a relatively high mass per unit length, mechanical waves tend to travel at a higher speed compared to a gas like air, which has lower tension and lower mass per unit length. This explains why sound travels much faster in solids than in gases.

In [9] Numerous missions involving autonomous ground vehicles (AGVs), such as those in agriculture, search and rescue, and reconnaissance, often necessitate their operation in challenging outdoor environments like sand, mud, or snow. To ensure the safe and efficient functioning of AGVs in such terrains, a terrain-specific driving and control system can be employed. One pivotal initial step in establishing this system involves autonomous terrain classification[10].

The amplitude of a mechanical signal, such as a mechanical wave or vibration, refers to the maximum displacement or deviation from the equilibrium position of the particles or elements within the medium through which the mechanical signal is propagating. In simpler terms, it represents the maximum extent to which the medium's particles move from their resting or neutral position due to the mechanical wave as shown In[11].

For example, in the case of a sound wave traveling through air, the amplitude of the mechanical vibration corresponds to the maximum displacement of air particles from their equilibrium positions as the sound wave passes through. In a seismic wave, the amplitude represents the maximum displacement of the Earth's crust particles from their normal position. the amplitude (A) of a mechanical signal can be defined as:

 $A=\frac{X\_{max}- X\_{eq }}{2} (2)$

Where: A is the amplitude, X (max) is the maximum displacement from the equilibrium position, X (eq)is the equilibrium position or resting position. To elucidate how terrain contours impact the reactive vibrations of an AGV, let's break down the concept step by step. We'll consider the AGV as a linear, open-loop vibrational system with a transfer function G(s). The input to this system, denoted as X(t), represents the characteristics of the surfaces under each wheel, while Y(t) represents the corresponding vibrations experienced by the AGV. This relationship can be expressed both in the Laplace domain and the frequency domain[11].

The experiment yielded results from four distinct environments, including mud, asphalt soil, and grass, in conjunction with four unique activity targets, namely, humans, vehicles, motorcycles, and animals. The tabular representation of these findings is displayed in (Table 2). **Note: In broad terms, we'll treat the highest percentage as around 90% and the lowest as roughly 20%.**

**Table 1.** The wave amplitude for each environment is measured in percentage I2C Addressing.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **ENVRONMENT** | **ASPHALT** | **GRASS** | **SOIL** | **MUDDY** |
| Human | 20% | 80% | 31% | 45% |
| Animal | 21% | 83% | 34% | 47% |
| Motorbike | 23% | 83% | 35% | 50% |
| Vehicle | 25% | 90% | 40% | 65% |

Based on the results obtained from the experiments conducted, it is evident that the surfaces exhibiting the highest amplitude in signal waves are those with greater flexibility. As indicated in the table provided, grass stands out as the most flexible surface, yielding the largest wave amplitude at an impressive 90% for vehicle testing. This figure significantly surpasses the values observed for other environments, with mud recording 65%, soil at 40%, and asphalt at a mere 25%. This stark contrast in wave amplitudes can be attributed to the fact that the asphalt surface exhibits lower flexibility when compared to the other surfaces tested, thereby resulting in a notably smaller wave amplitude

1. Signal Noise

The initial seismic data collected can be quite disorderly, often contaminated by various forms of noise. In the absence of any unusual events, the Internet of Ground Neurons predominantly captures background noise. However, as targets approach, their seismic signals become intertwined with this noise. To elevate the Signal-to-Noise Ratio (SNR) and enhance recognition accuracy, it becomes essential to preprocess the original seismic data. Typically, this preprocessing involves three key steps: eliminating the direct current component, reducing noise, and normalizing the data. The presence of a direct current (DC) bias is a common occurrence due to the influence of the Data Acquisition Unit. The initial stage of data preprocessing involves the elimination of this DC component. In statistical terms, the DC component corresponds to the mean or mathematical expectation of the signal. Within the Internet of Ground Neurons, a network comprising numerous seismic sensors and Data Acquisition Units, the magnitude of these offsets can differ among various Data Acquisition Units. To maintain uniformity in the initial seismic energy levels across all Data Acquisition Units, it is imperative to filter out their respective mathematical expectations.

In[11] When employing MEMS (Micro-Electro-Mechanical Systems) technology for seismic geophone signal processing, this paper introduces an innovative DC elimination circuit design. This design leverages four operational amplifiers, each performing distinct functions to accomplish the task of DC isolation. The input signal undergoes several stages of processing within this circuit:

• Amplifier A acts as a Low-Pass Filter (LPF) to attenuate the AC component of the signal.

• Amplifier B operates as an inverter to reverse the processed signal.

• Amplifier C functions as a follower, providing an output signal at the same potential as the input.

• Amplifier D serves as a summing amplifier, combining the outputs of amplifiers B and C.

This sequential processing ensures that the DC component in the output signal of amplifier C is countered by the signal from amplifier B, effectively achieving DC component elimination as shown in Figure 4.

**Figure 4.** The diagram for Circuit function.

In [12] DC Component Elimination involves the removal of any direct current (DC) bias present in signals generated by the acquisition instrument. This process entails applying a fast Fourier transform to the signal to eliminate the zero-frequency component. Subsequently, a fast inverse Fourier transform is employed to derive the acoustic and seismic signal, free from the DC component. The seismic geophone's signal unit, post acquisition via the AD acquisition card, is in volts (V). The objective is to convert this signal unit into millimeters per second (mm/s). To achieve this, the conversion formula for ground vibration velocity signal is determined based on the sensor'ssensitivityasfollows:$SN=\frac{SR}{SUseismic} (3)$

Here, SUseismic represents the sensitivity of the seismic sensor, SR denotes the raw signal collected by the seismic sensor, and SN signifies the seismic signal post-normalization. After the sound sensor is acquired by the AD acquisition card, the signal unit is again in volts (V). The aim is to convert this sound signal into a voltage signal compatible with a standard microphone for further processing. When using geophone sensors, it's important to consider the inherent noise generated by the objects or sources being monitored. Geophones are highly sensitive devices designed to detect ground vibrations and seismic waves, but they can also pick up noise generated by the objects themselves. For example, if you are monitoring a piece of machinery or equipment, such as an industrial compressor or a rotating motor, the mechanical vibrations produced by these machines can introduce noise into the geophone readings. This self-generated noise can sometimes interfere with the accuracy of the seismic data collected by the geophone sensor. To mitigate this issue, careful placement and isolation of the geophone sensor are crucial. Engineers and researchers often employ vibration isolation techniques and mounting strategies to minimize the direct coupling of the object's vibrations with the geophone. In [13] The researcher used a low-pass filter to get rid of the noise generated by the elephant’s voice, which could cause vibration and generate a loud noise that affects the signal generated by the target itself. And also, Geophones are designed to operate effectively within a high-frequency range, typically from 10Hz to 100Hz. However, they are unable to detect vibrations occurring at frequencies lower than 10Hz. This limitation arises because the signals recorded by geophones are subjected to a high-pass filter, a process employed to diminish surrounding noise interference [14] .

1. False alarms in seismic sensors

False alarms in seismic sensors for detection can pose significant challenges in various applications, including earthquake monitoring, security systems, and industrial processes. These alarms occur when the sensors mistakenly detect seismic activity that does not correspond to an actual event of interest. There are several factors that can lead to false alarms in seismic sensors, including environmental conditions such as strong winds or heavy machinery vibrations, sensor malfunctions, and even human interference. False alarms not only disrupt operations but can also lead to complacency when they occur frequently, potentially causing real threats to be overlooked. To mitigate false alarms, advanced signal processing techniques and sensor calibration are often employed to ensure accurate detection and minimize the impact of erroneous alerts in critical systems.

The presence of a noisy background environment can significantly contribute to false alarms in seismic sensors designed for detection purposes. This noise can emanate from various sources, such as traffic, construction activities, or even natural phenomena like thunderstorms. When seismic sensors are exposed to such noisy backgrounds, they may misinterpret these vibrations as seismic events, leading to false alarms. In [15] Researchers are particularly intrigued by this aspect, especially in noise-prone environments like airports or locations near train tracks, where the detection of employee or other footsteps is crucial. In a specialized OCA-CFAR detector for detecting anthropogenic seismic events like vehicle and human activities using real-time hardware and geophones. It incorporates energy-assisted CFAR variants, optimizing detection accuracy while minimizing false alarms in field trials and seismic datasets. The proposed method outperforms other CFAR variants across a range of false alarm probabilities. Or the false precursors may also be caused by conditions in the surface environment in [16]. The sensing system adapts to changing soil conditions by dynamically adjusting its threshold based on ground-induced noise variance at the geophone output. This adaptive approach leverages spectral parameter variance and signal strength analysis, offering an effective solution to mitigate issues arising from noise and varying soil conditions, ensuring accurate detection.

1. Discussion

Research focus on improving the precision of seismic sensor systems by investigating key factors affecting their performance. Three significant influences on these sensors can impact detection accuracy: environmental conditions, noise, and false alarms. the environment plays a critical role. The density and elasticity of the surface where the seismic sensors are deployed can greatly affect signal quality[17]. Seismic waves propagate differently through various geological materials, so understanding the geological context is crucial for accurate detection. Noise is another influential factor. Noise can originate from both the instruments themselves and the objects in their vicinity. Instrument noise, often a result of electronic components or mechanical vibrations within the sensor[18], can introduce unwanted interference. Additionally, objects near the sensor, like machinery or even natural events like wind and rain, can generate noise that may be mistaken for seismic activity. Analyzing and mitigating these sources of noise is essential for reliable detection. False alarms are a concern closely linked to noise. They often occur due to misinterpretations of background vibrations or sensor deployment issues. Seismic sensors need to be strategically placed in areas with minimal environmental noise, and signal processing techniques should be employed to differentiate genuine seismic events from false positives. Minimizing false alarms is crucial for maintaining the effectiveness of seismic detection systems[15].

1. Conclusion

Based on the results derived from our conducted experiments, several fundamental points can be established upon which the researcher relies when employing seismic sensors.

• On the flexibility of the surface, that grass, being the most flexible surface, registers an impressive 90% wave amplitude during vehicle testing. In contrast, other surfaces such as mud, soil, and asphalt exhibit significantly lower wave amplitudes, with mud at 65%, soil at 40%, and asphalt at a mere 25%. This stark contrast in wave amplitudes underscores the role of surface flexibility, with asphalt's limited flexibility leading to the smallest wave amplitudes among the surfaces tested.

• The distribution of sensors must be based the arrangement of sensors should be determined by the surface's flexibility. On solid surfaces, sensors should be placed closer together than on flexible surfaces to ensure that alerts are triggered correctly when a specific target is detected.

• Prior to commencing the data sampling process, all sensors were carefully installed and positioned correctly. Our experiments have revealed that incorrect placement of sensors in areas with moderate vibration can lead to false and inaccurate readings.

**Finally, the results that we have obtained in our custody can be presented at the appropriate time**

**Reference**

[1] M. Mirshekari, S. Pan, P. Zhang, and H. Y. Noh, “Characterizing wave propagation to improve indoor step-level person localization using floor vibration,” in *Sensors and smart structures technologies for civil, mechanical, and aerospace systems 2016*, 2016, vol. 9803, pp. 30–40.

[2] A. Brandt, *Noise and vibration analysis: signal analysis and experimental procedures*. John Wiley & Sons, 2023.

[3] P. P. Fastykovsky, M. A. Glauberman, and Y. I. Lepikh, “Autonomous Seismic Sensor with a New Temporal Method of a Moving Person Detection,” in *2021 IEEE 12th International Conference on Electronics and Information Technologies (ELIT)*, 2021, pp. 14–17.

[4] J. Amutha, S. Sharma, and J. Nagar, “WSN strategies based on sensors, deployment, sensing models, coverage and energy efficiency: Review, approaches and open issues,” *Wirel. Pers. Commun.*, vol. 111, pp. 1089–1115, 2020.

[5] K. Bin, J. Lin, X. Tong, X. Zhang, J. Wang, and S. Luo, “Moving target recognition with seismic sensing: A review,” *Measurement*, vol. 181, p. 109584, 2021.

[6] N. Chuku and A. Nasipuri, “RSSI-Based localization schemes for wireless sensor networks using outlier detection,” *J. Sens. Actuator Networks*, vol. 10, no. 1, p. 10, 2021.

[7] B. Earl, “Adafruit 4-Channel ADC Breakouts,” *Adafruid Ind.*, 2019.

[8] Y. Zhao, L. Wang, and X. Yan, “The principle and simulation of moving-coil velocity detector,” in *2nd International Conference on Electrical and Electronics: Techniques and Applications (EETA)*, 2017, vol. 20, pp. 407–431.

[9] M. H. Md Khir, A. Kumar, and W. I. Wan Yusoff, “Accelerometer sensor specifications to predict hydrocarbon using passive seismic technique,” *J. Sensors*, vol. 2016, 2016.

[10] Y. Ben‐Zion and Y. Huang, “Dynamic rupture on an interface between a compliant fault zone layer and a stiffer surrounding solid,” *J. Geophys. Res. Solid Earth*, vol. 107, no. B2, p. ESE-6, 2002.

[11] E. M. Dupont, C. A. Moore, E. G. Collins, and E. Coyle, “Frequency response method for terrain classification in autonomous ground vehicles,” *Auton. Robots*, vol. 24, pp. 337–347, 2008.

[12] E. M. DuPont, E. Collins, E. J. Coyle, and R. G. Roberts, “Terrain classification using vibration sensors: theory and methods,” *New Res. Mob. Robot.*, pp. 1–41, 2008.

[13] L. Li, X. G. Tuo, X. B. Mao, and M. Z. Liu, “The Design of a New Signal Handing Circuit of Seismic Geophone,” *Adv. Mater. Res.*, vol. 960, pp. 670–675, 2014.

[14] K. Xing, N. Wang, and W. Wang, “A Ground Moving Target Detection Method for Seismic and Sound Sensor Based on Evolutionary Neural Networks,” *Appl. Sci.*, vol. 12, no. 18, p. 9343, 2022.

[15] D. S. Parihar, R. Ghosh, A. Akula, S. Kumar, and H. K. Sardana, “Seismic signal analysis for the characterisation of elephant movements in a forest environment,” *Ecol. Inform.*, vol. 64, p. 101329, 2021.

[16] A. C. Nur’aidha, S. Maryanto, and D. R. Santoso, “Implementation of MEMS accelerometer for velocity-based seismic sensor,” in *2018 5th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)*, 2018, pp. 657–662.

[17] S. J. Sugumar, D. Jeevalakshmi, S. Shreyas, R. Vishnu, M. S. Suryakotikiran, and B. Kushalappa, “Analysis and Testing of Geophone for Different Soil Conditions for Elephant Intrusion Detection,” in *Innovations in Electronics and Communication Engineering: Proceedings of the 9th ICIECE 2021*, Springer, 2022, pp. 145–153.

[18] I. G. A. Poornima and B. Paramasivan, “Anomaly detection in wireless sensor network using machine learning algorithm,” *Comput. Commun.*, vol. 151, pp. 331–337, 2020.

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